Charles University in Prague
Faculty of Social Science
Institute of Economic Studies

BACHELOR THESIS

The effect of exchange rate changes on stock market volatility in New Member states

Prague 2010 **Radek Janhuba**

Charles University in Prague
Faculty of Social Science
Institute of Economic Studies

BACHELOR THESIS

The effect of exchange rate changes on stock market volatility in New Member states

Author: Radek Janhuba

Supervisor: Roman Horváth, M.A., Ph.D.

Academic Year: 2009/2010

Declaration

I declare that I wrote this thesis myself and used only the literature listed in References.

V Praze dne ______________ ____________________

podpis

Acknowledgments

I would like to thank my supervisor, Roman Horváth, M.A., Ph.D., for his time, suggestions and valuable comments.

Abstract

This thesis examines whether currency exchange rate changes play any role in determination of stock market volatility in the EU's New Member states. Using the daily data of six Central and Eastern European countries, we run a GARCH model including the exchange rate variable into the volatility equation. Using a TARCH model we also examine whether the magnitude of stock market volatility depends on the direction of last innovation. The results suggest that an exchange rate depreciation will boost stock market volatility in Czech Republic, Hungary and Poland, whereas the same applies for currency appreciation in Romania. The various results for various countries are in line with the previous research.

Title:	The effect of exchange rate changes on stock market volatility in New Member states
Author:	Radek Janhuba
Author's e-mail:	janhuba@gmail.com
Supervisor:	Roman Horváth, M.A., Ph.D.
Supervisor's e-mail:	roman.horvath@gmail.com
Academic year:	2009/2010
JEL Classification:	C22, G15 , F31
Keywords:	Stock market volatility, GARCH, Exchange rate

Abstrakt

Tato práce zkoumá, zda změny ve směnném kurzu hrají roli v určení volatility akciového trhu v nově členských státech EU. S použitím denních dat z šesti zemí střední a východní Evropy zkoumáme GARCH model, do kterého přidáváme změnu směnného kurzu jako vysvětlující proměnnou do rovnice volatility. Použitím TARCH modelu také zkoumáme, zda volatilita akciového trhu závisí na znaménku jeho poslední změny. Výsledky ukazují, že oslabení směnného kurzu posiluje volatilitu akciového trhu v České republice, Maďarsku a Polsku, zatímco v Rumunsku dojde ke stejnému výsledku po posílení směnného kurzu. Odlišnost výsledků pro různé země je v souladu s výsledky předchozích výzkumů.

Název práce:	Vliv změn směnného kurzu na volatilitu akciového trhu v nově členských státech EU
Autor:	Radek Janhuba
E-mail autora:	janhuba@gmail.com
Vedoucí práce:	Roman Horváth, M.A., Ph.D.
E-mail vedoucího práce:	roman.horvath@gmail.com
Akademický rok:	2009/2010
Klasifikace JEL:	C22, G15 , F31
Klíčová slova:	Volatilita akciového trhu, GARCH, směnný kurz

Contents

List of Tables

Chapter 1

Introduction

After the crash of Bretton Woods fixed exchange rate system in the early 1970s, volatility of exchange rates has significantly increased. Moreover, volatility of stock returns was found to increase as well (Bartov et al., 1996). Whereas the former outcome is not surprising at all, as the volatility of fixed exchange rates is held minimal by principle, the second phenomenon raised the question whether or not the exchange rate regime shift represented the starting mechanism for the increase.

The theoretical and empirical research has not stayed with the previous question. Firstly, economists tried to find the relationship between the levels of exchange rate changes and stock returns. In the recent years, they also shifted their attention to the relationship between the second moments of these variables.

This thesis tries to find the impact that exchange rate changes have had on the stock market volatility in the New Member states of the European Union. The so called New Member states are the ones that joined the European Union in April 2004 and January 2007. Those countries are (in alphabetical order) Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia.

The period of our interest lies between the years 1999 and 2009. The beginning of the period was chosen because of the introduction of Euro with the beginning of 1999. The end of the period was limited due to a time needed to perform the analysis.

Unfortunately, because it is hardly possible to study impacts of change of a variable that does not change, we had to cross out the currencies that were fixed during our period of interest. Therefore we had to abandon the analysis of Bulgaria, Estonia, Latvia and Lithuania. As we need to analyze floating currencies, we also had to shorten the time span of Slovakia and Slovenia. More information is provided in section 4.1.

Unfortunately we were not able to find any relevant empirical research that would examine either level or volatility relations between exchange rates and stock indices in any country of our attention. Therefore we expect to find whether (and how) the exchange rate changes influence the stock market volatility in our countries.

The rest of this thesis is organized as follows. Chapter two presents a brief overview of empirical research done so far, for both direct relations and volatility spillovers. Chapter three presents an overview of the most important terms and methods of time series econometrics and explains our econometric techniques. Chapter four describes the data and tests their properties. Chapter five presents three different ARCH class models, their results and interpretations. Chapter six concludes and offers ideas for future research.

Chapter 2

Literature overview

Although economists have been trying to find solutions to the relationship between exchange rates and stock market since the 1970s, they have not generally been able to find a conclusive evidence until the 1990s (Ajayi & Mougoue, 1996, p.194). This section reviews empirical research of the exchange rate and stock price interactions in various countries and various time spans. The studies reviewed here use various econometric techniques. Some of them found a significant economic relationship and some of them did not.

Various papers also differ in the purpose to find either a short or long term relationship between the two variables. Because it is appropriate from the time series techniques point of view, we will mainly concentrate on the short term relations.

2.1 Direct relationship

The first notable study is the one of Ma & Kao (1990). The authors find that stock markets react to the exchange rate changes based on whether the economy is import or export dominant. For the import dominant countries they suggest that currency appreciation will boost the stock market. On the other hand, the exporters of the export dominant economy will lose their competitive power in the event of currency appreciation, which will lead to the stock market fall. Even though this result is interesting, we, however, can not rely on it as the authors used monthly data. They also used a two stage regression, which is not an appropriate method when the data are not normal.

Dimitrova (2005) uses the 2 Stage Least Squares regression to examine the relationship of US stock market and US-UK exchange rate. She comes to a conclusion that the relationship between stock prices and exchange rate is ambiguous, suggesting a positive correlation when stock prices are the first to move and a negative one in the other direction. However, only few coefficients of her model are statistically significant.

Ajayi & Mougoue (1996) find the same result as Ma & Kao (1990) using an Error Correction Model, supporting the argument that currency depreciation leads to a decrease in the stock market. However, there is a difference between the two articles, as Ajayi and Mougoué do not restrict their findings to import dominant economies. Moreover, they also find a significant negative relationship between the exchange rate and stock market for the short-run effect.

On the other hand, the research of Nieh & Lee (2001) contradicts most of the previous studies, suggesting that no long-run relationship exists between the exchange rates and stock markets for all G-7 countries. They do, however, find a significant one day effect for three out of the seven countries. According to their results the local currency depreciation will stimulate the stock market in Canada and United Kingdom, whereas it will drag down the market in Germany.

Similarly, Alaganar & Bhar (2007) use a GARCH-M model to examine a short-term influence of exchange rates on WEBS stock indices in sixteen developed countries. They find a significant relationship for eight of their countries. Their results are compatible with the results of Nieh & Lee (2001) in case of Canada, France, Italy and United Kingdom, whereas they contradict the results for Germany and Japan. However, it is possible that the stock market properties have changed as Nieh & Lee (2001) focus on the period of October 1993 until February 1996 and Alaganar & Bhar (2007) examine the time span of March 1996 to December 2000.

The previous studies concentrated on highly developed countries with a long history of its stock markets. However, as the history of stock exchanges in the new member states does not go any deeper than twenty years, there is a question if these stock markets can be considered developed. The liquidity of our markets is undoubtedly lower than the liquidity of the markets observed in the studies above.

On the other hand, the excess returns of individual stocks are usually not as high as in case of the so called emerging markets. That is why it is hard to decide whether the new member states' stock markets should be considered emerging or not. The next paragraphs review the studies observing relationship between exchange rates and stock market in emerging economies.

There is a decent number of studies particularly concentrating on the East Asian region in the late 1990s. After the 1997 crisis, the currencies and stock markets depreciated rapidly throughout the region. Numerous studies have been taken to find out which was the leading variable of the downturn. However, the results of these studies is quite inconclusive, suggesting very different results for various countries.

For example, Granger et al. (2000) examine the relations of echange rates and stock market for nine East Asian countries. They find a significant relationship from the exchange rate to stock market only in the case of South Korea. In cases of Hong Kong and Phillipines they find a relationship of the other direction and for Malaysia, Singapore, Thailand and Taiwan they find a significant bidirectional relationship where, however, it is not possible to identify which variable is the leading one. On the other hand, Abdalla & Murinde (1997) study the exchange rate and stock price interactions for the Asian countries prior to the crisis (specifically from January 1985 to July 1994) and examine the unidirectional causality from exchange rates to stock market.

Aydemir & Demirhan (2009) find a negative causal relationship from exchange rate to five different stock indices in Turkey. On the other hand, Kasman (2003) finds the existence of this relationship only in case of the industry sector index.

Despite extensive research conducted, there is still no up-to-date consensus among economists about the relationship of exchange rates and stock markets. The following paragraph taken from Aydemir & Demirhan (2009) provides a nice summary of the situation:

> *Economists have tried to explain exchange rates-stock price nexus for a long time. There have been many empirical and theoretical studies to define the direction of causality between these two financial variables. However, the di-*

rection of causality still remains unresolved in both theory and empirics. While some empirical studies find some relations and causality, other studies show no causality between these two variables. Moreover, direction of causality changes from one economy to another. Also, the empirical studies for a specific economy may show different results for this relation. The reason for these differences can be explained by time period used for data, econometric models used and economic policies of countries.

2.2 Volatility spillovers

Because of the presence of contradicting results in empirical literature we will try to examine the relationship between exchange rates and stock market from another point of view. Specifically we will try to find out whether a change in exchange rate level has any implications into the stock market volatility.

Bartov et al. (1996) find out that the increased volatility of stock returns for US multinational companies was caused by the increase of dollar exchange rate variability after the collapse of Bretton Woods system. Even though they aim their research into individual companies, they also find a significant relationship for equally weighted portfolios of their sample firms.

De Santis & Gérard (1998) use monthly data for the period from 1973 to 1993 to examine potential existence of currency risk premia in stock market returns for USA, Germany, United Kingdom and Japan. They run a multivariate GARCH model and find out that the currency risk premiums are present in the data, however, they notably vary accross time and countries. On the other hand, they find a significant negative currency risk premia for the period between January 1980 and December 1985, whereas a positive risk premium is found in the period of January 1989 to December 1994.

Alaganar & Bhar (2007) run a GARCH-M model to search for possible influence of exchange rate's conditional volatility on the WEBS stock indices' volatility. They find presence of significant positive spillover in eight of sixteen researched countries.

To the contrary, Kanas (2000) examines the volatility spillovers between exchange rate changes and stock returns in the same countries as De Santis & Gérard (1998) plus France and Canada, in the period from January 1986 until February 1998. He uses a multivariate EGARCH model and finds out that there are no significant volatility spillovers from exchange rates to stock indices.

On the other hand, Choi et al. (2007) use the very similar EGARCH model to find significant spillovers from exchange rates to stock market in the case of New Zealand both before and after the 1997 crisis.

Kyung-Chun (2008) finds out that the local equity market volatility was significantly increased by the exchange rate fluctuations in eight East Asian countries in the period from July 1994 until August 2001. This relationship was especially strengthened during the Asian financial crisis. He also finds out that the relationship between exchange rates and stock indices is stronger in case of Asian variables compared to the case of US.

Chapter 3

Time series econometrics

The main characteristics of a time series data is that the values of observations in period t are directly or indirectly related to values at previous periods. This chapter seeks to show the specifics of time series econometric analysis used in this thesis. We will start with explanation of the basic terms and we will go through the theory needed to understand the concept of the model used to fit the data. The main background for this chapter are Verbeek (2008), Tsay (2002), Hamilton (1994) and Brooks (2008).

3.1 Basic terms

Consider a time series $\{y_t\}$. Generally we distinguish two classes of time series processes, deterministic and stochastic. A deterministic process y_t follows a path

$$y_{t+1} = F(t)$$

where $F(t)$ is a function of time which does not contain a random process. Therefore no random effects are present in a deterministic time series. However, because the vast majority of empirical variables can be described as stochastic processes we will not consider deterministic approach in the rest of this thesis.

A stochastic process means that individual observations are picked from a probability distribution and are therefore random variables. The basic and simplest stochastic process is the white noise.

Definition 3.1 (White noise): A stochastic process ε_t is called a white noise process if the following conditions are satisfied:

$$\begin{aligned} &E\left(\varepsilon_t\right) = 0 \\ &E\left(\varepsilon_t^2\right) = \sigma^2 \\ &E\left(\varepsilon_t \varepsilon_u\right) = 0, t \neq u \end{aligned} \tag{3.1}$$

The white noise process is the most important building block of all series described in this thesis. Another important example of a simple stochastic process is a random walk process following the equation

$$y_{t+1} = y_t + \varepsilon_t \tag{3.2}$$

where ε_t is a white noise process.

3.1.1 Stationarity

One of the most important characteristics while analyzing time series data is stationarity. By examining a relationship between two nonstationary variables, there is a danger one would examine a significant statistical relationship while there in fact is no real dependence between the variables. This result is reffered to as a spurious regression and its danger has been introduced by Granger & Newbold (1974).

Definition 3.2 (Stationarity): A series $\{y_t\}$ is stationary if

$$\begin{aligned} &E\left(y_t\right) = \mu \\ &E\left(y_t - \mu\right)\left(y_{t-l} - \mu\right) = \gamma_l \end{aligned} \tag{3.3}$$

Variable γ_l from the previous definition is the covariance of a variable in time t and its own value in time $t - l$. It is called the l-th lag autocovariance and has a crucial position in the autocorrelation function defined below.

To be in consensus with the usual theorethical literature, it is important to remark that this definition of stationarity is usually called *weak stationarity*. There also is a concept of *strong stationarity* which marks that the joint distribution of $\{y_t\}$ is exactly the same as the joint distribution of $\{y_{t+s}\}$ for all s.[1] However, there is no empirical concept how to test for the presence of strong stationarity, so we use the general term stationarity for the concept of weak stationarity.

Many empirical time series do not fall into the category of stationarity. This can be very often corrected by differencing them. A series marked as $I(n)$ where n is a positive integer is said to be intergrated of order n, meaning the series has to be differenced n times to become stationary. Therefore an $I(0)$ series is stationary. An $I(1)$ is said to contain one unit root[2].

There are several different ways how to test for the presence of stationarity or unit root in the data. For a comprehensive review of these tests, see section 8.4 of Verbeek (2008). The most widespread test of these is the Augmented Dickey-Fuller (ADF) test developed by Dickey and Fuller. This test performs the null hypothesis of one unit root against an alternative of stationarity. However, there is a need to select the appropriate lag length. In order to avoid this lag selection procedure we have decided to use the Phillips-Perron test instead. This test uses the Newey-West standard errors to account for the potential autocorrelation pattern in the errors (Verbeek, 2008). To confirm our findings from the other side of view we also run the KPSS test with 15 lags which tests the null hypothesis of stationarity against the alternative of unit root.

3.1.2 Autocorrelation

Let us now remind a general correlation coefficient ρ which is defined as

$$\rho\,(X,Y) = \frac{cov\,(X,Y)}{var(X)\cdot var(Y)} \tag{3.4}$$

[1]In other words, the distribution of $\{y_t\}$ is invariant to any time shift

[2]The explanation of a unit root is provided below

The autocorrelation coefficient follows the same principle, where it observes the correlation of the the series with itself shifted in time.

Definition 3.3 (Autocorrelation): The coefficient

$$\rho_l = \frac{cov\left(y_t, y_{t-l}\right)}{var\left(y_t\right)} = \frac{\gamma_l}{\gamma_0} \tag{3.5}$$

is called the l-th lag autocorrelation coefficient of $\{y_t\}$. ▶

The sequence $\rho_0, \rho_1, \rho_2, ...$ is called the autocorrelation function (ACF). Because we can see that $\rho_0 = 1$ for all series directly from the definition 3.3, we will be interested in the ACF starting from the first lag. As we will see below, ACF can be very valuable while finding the right type of model used to describe the data.

3.2 ARMA models

There are two basic interpretations of how to describe a time series process: Autoregressive and moving average principle. Firstly we describe the autoregressive series and its conditions, then we show the moving average series and its conditions and then we combine the two together.

3.2.1 Autoregressive processes

The idea of autoregressive process states that the value of the series directly comes from its value in previous periods. Let us first consider the first-order process, AR(1). It follows the equation

$$y_t = \phi_0 + \phi_1 y_{t-1} + \varepsilon_t \tag{3.6}$$

where ϕ_0 is a constant, ϕ_1 is a coefficient of any value and ε_t is a white noise process. The autocorrelation function of the AR(1) process takes the form $\rho_l = \phi_1^l$ (Tsay, 2002).

Therefore, it directly follows that in case that $|\phi_1| \geq 1$ the ACF grows to infinity, which results to the nonstationarity of $\{y_t\}$. On the other hand, if $|\phi_1| < 1$, it can be shown that $\{y_t\}$ is weakly stationary (Hamilton, 1994). The ACF is still represented by $\rho_l = \phi_1^l$, so its graph exponentially decays to zero.

Let us now recall the random walk process described by the equation 3.2. It is a special case of the AR(1) where $\phi_0 = 0$ and $\phi_1 = 1$. If we allow ϕ_0 to take any value, the process can be transformed to the form

$$\Delta y_{t+1} = \phi_0 + \varepsilon_t \tag{3.7}$$

where Δ marks first-difference operator. The coefficient ϕ_1^* of the new series $\{\Delta y_t\}$ equals zero so the new series is stationary. This confirms that in case that a series follows the random walk, it can be transformed to a stationary one by taking its first difference.

Generally, an autoregressive process of order p, AR(p), is represented by an equation

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \tag{3.8}$$

where ϕ_0 is a constant, ϕ_i are coefficients of any value and ε_t is a white noise process. In order to observe the properties of this process, we need to solve the characteristic equation which takes the form

$$x^p - \phi_1 x^{(p-1)} - \phi_2 x^{(p-2)} - \ldots - \phi_p = 0 \tag{3.9}$$

The solutions of the characteristic equation are called characteristic roots. The series is stationary if and only if $\prod_{i=1}^{p} \phi_i < 1$ (Tsay, 2002).

3.2.2 Moving average processes

The idea of the moving average approach is that instead of the values from the previous periods, the series is dependent on the errors in the previous periods. Thus, a general moving average process of order q is described as

$$y_t = \theta_0 + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{3.10}$$

where θ_is are coefficients of any value and ε_t is white noise. Thus, the MA series consists only of fixed coefficients and white noises. From the definition of white noise we can see that its mean is zero and all covariances are finite. As a result the MA(q) process will always be stationary. Important characteristics of the MA(q) process is its ACF function since the $\rho_l = 0$ for all $l > q$. Therefore it is easy to obtain an order of MA process from the sample ACF function while fitting the model.

3.2.3 ARMA processes

The autoregressive moving average models combine properties of AR and MA models. This combination can be useful because it allows to describe the data while keeping quite a low amount of parameters. ARMA models have been found to provide very good alternative to OLS in case of time series analysis. Moreover, Tsay (2002, p.93) shows that a GARCH model described below can be seen as a nonstandard ARMA model.

Generally, an ARMA(p,q) model is described by equation

$$y_t = c_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{3.11}$$

where c_0, ϕ_i and θ_j are coefficients of any value. Because, as seen above, the MA processes are always stationary, the stationarity of the ARMA model is dependent on its AR part. Therefore we need to observe the same characteristic equation as in AR model:

$$x^p - \phi_1 x^{(p-1)} - \phi_2 x^{(p-2)} - \ldots - \phi_p = 0 \tag{3.12}$$

Again, if the product of all characteristic roots is less than one, the ARMA(p,q) series is stationary.

3.2.4 ARIMA

To ensure consensus with usual time series literature we need to describe also the Autoregressive Integrated Moving Average models. A process $\{y_t\}$ follows an ARIMA(p,d,q) specification in the case that it is

1. an I(d) process, and

2. a process $\{z_t\}$, $z_t = \Delta^d y_t$ follows an ARMA(p,q) process

ARIMA principle is simply a generalization of ARMA process. In case some empirical variable follows ARIMA process, it is differenced into an ARMA one and the rest of the analysis is made. Therefore the necessary conditions are exactly the same as for ARMA models.

3.3 Conditional heteroskedasticity

When researchers started to estimate the variance of processes, they had no dynamic framework how to model it. One of the issues was that as there usually is only one observation a day available, the volatility of e.g. a stock is not directly observable (Tsay, 2002, p.80). The usual consensus on how to avoid this complication was to use the *historical volatility* approach, where volatility is calculated as the sample standard deviation in selected period (Engle, 2003).

However, these estimates were shown to vary with different periods and different time lenghts. Furthermore, it has been shown that volatility tends to cluster together, meaning that the observations with low and high changes tend to stick together in time. The conditional heteroscedasticity models allow forecasts of variance to dynamically change over time and are therefore extremely valuable while modelling volatility of the data.

Before we start to describe ARCH class models, we need to note a test for heteroscedasticity. This is usually done by examining the autocorrelation function of the series and squared series. The null hypothesis of no ARCH effect would be confirmed in case that the ACF coefficients would be statistically insignificant. Rejecting this hypothesis confirms that ARCH effects are present in the data.

The Ljung-Box test statistic is also often used to check for the presence of autoregressive heteroscedasticity in the data. A highly significant Ljung-Box test statistic of squared series means that the data is not white noise. Furthermore, it can be interpreted as a proof of volatility clustering (Scheicher, 2001, p.30).

3.3.1 ARCH models

Autoregressive Conditional Heteroskedasticity principle has been developed by Robert Engle in 1979. In Engle (1982) he introduced a time-varying conditional variance of the dependent variable (conditional upon the past observations) while still assuming its constant unconditional variance. The basic idea is that the variance of the process can be modelled by taking a weighted average of its past squared residuals (Engle, 2003). The original set of equations describing the simplest ARCH model has a form of

$$\begin{aligned} y_t &= \varepsilon_t \sqrt{h_t} \\ h_t &= \alpha_0 + \alpha_1 y_{t-1}^2 \end{aligned} \tag{3.13}$$

where ε_t is a white noise process, α_0 and α_1 are coefficients and h_t is the conditional variance of variable y_t. This specification is called an ARCH(1) model. Engle (1982) also shows generalized ARCH(p) model which can be formally described as

$$\begin{aligned} y_t|\Psi_{t-1} &\sim N\left(0, h_t\right) \\ h_t &= h\left(y_{t-1}, y_{t-2}, \ldots, \alpha\right) \end{aligned} \tag{3.14}$$

where Ψ_{t-1} is the information set available at time $t-1$, p is the order of ARCH process and α is a $(p+1)$ dimensional vector of parameters. Fitting the model onto a standard OLS regression, we obtain

$$\begin{aligned} y_t|\Psi_{t-1} &\sim N\left(x_t\beta, h_t\right) \\ h_t &= h\left(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-p}, \alpha\right) \\ \varepsilon_t &= y_t - x_t\beta \end{aligned} \tag{3.15}$$

Usually the function $h(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-p}, \alpha)$ takes form of a simple linear function, which allows us to write the ARCH(p) process by a set of equations

$$\begin{aligned} &\varepsilon_t \sim N(0, h_t) \\ &h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}, \end{aligned} \tag{3.16}$$

where $\alpha_0 > 0$ and $\alpha_i \geq 0$ for the variance to be non-negative. To ensure stationarity, we have to impose a restriction that $\sum_{i=1}^{p} \alpha_i < 1$. If this condition is satisfied, the unconditional variance of the process takes the form

$$\sigma^2 = \frac{\alpha_0}{1 - \sum_{i=1}^{p} \alpha_i}. \tag{3.17}$$

Although the standard OLS procedure has been used by Engle (1982) in this case, it is not the only case where the ARCH model works. As the only restriction for the mean equation is that it includes the residual part and a constant, we can use another specifications to fit the data, including an ARMA model. The model then calculates volatility forecasts for every period of the sample. Coefficients $\alpha_1, \alpha_2, \ldots, \alpha_p$ are found using the Maximum Likelihood procedure in such a way that the forecasts are as close as possible to the real values in the forecasted period (Engle, 2003).

To check for ARCH effects in the data we follow the Engle's Langrange Multiplier test first described by Engle (1982, p.1000). At first, we estimate the mean equation and save its residuals ε_t. To estimate whether there is a presence of ARCH(p), we then regress these residuals on constant and p lagged values using the standard OLS procedure:

$$\varepsilon_t = \gamma_0 + \gamma_1 \varepsilon_{t-1} + \gamma_2 \varepsilon_{t-2} + \ldots + \gamma_p \varepsilon_{t-p} + \omega. \tag{3.18}$$

Then we take the R^2 statistics of the regression and multiply it with number of observations T. The resulting test statistics TR^2 follows the chi-square distribution with p-degrees of freedom: $TR^2 \sim \chi^2_p$. The null hypothesis of the test is that there are no ARCH effects present in the data. Rejection of H_0 therefore confirms its presence.

3.3.2 GARCH models

Engle's ARCH model provided a huge improvement in modelling of the volatility of the data. However, while analyzing high-frequency data, the autocorrelation of ε_t^2 was found to decay only slowly, entailing the need of a very long order of ARCH process (Nobel Prize Committee, 2003).

The solution is presented by the so called Generalized Autoregressive Conditional Heteroskedasticity, GARCH. It was developed by Tim Bollerslev, Engle's graduate student, in Bollerslev (1986). The main idea is that in case of need for a long order of ARCH process, a decent number of those processes can be substituted by the volatility estimation from previous periods (as those processes are represented in that equations as well). The standard GARCH(p,q) model is presented by the set of equations

$$\begin{aligned} &\varepsilon_t|\Psi_{t-1} \sim N\left(0, h_t\right) \\ &h_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \end{aligned} \tag{3.19}$$

In case that $j = 0$ the process becomes an ARCH(p) process. In most of the cases it is enough to set $j = 1$. That is the reason why GARCH(1,1) model became the most widespread conditionally heteroskedastic model in financial practice. It is usually sufficient enough to describe the volatility of almost any return series in finance. Furthermore, it holds for most of the types of stocks, equity indices, exchange rates or bond returns (Engle, 2003). The volatility equation of the GARCH(1,1) model takes the form

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{3.20}$$

and its coefficients can be interpreted as the following three properties of the data (Brooks, 2008, p.392):

1. α_0 represents the long run average variance of the data,
2. $\alpha_1 \varepsilon_{t-1}^2$ shows the most recent squared residual, which contains the new information obtained in the last period,
3. and $\beta_1 h_{t-1}$ represents the variance forcast for the previous period.

The forecast for period t is then counted as a weighted average of the above three variables (Engle, 2001). Similarly as in the ARCH estimation, this procedure is performed using a Maximum Likelihood approach.

The GARCH theory is in fact generalized ARCH. In fact, Brooks (2008, p.393) shows that the GARCH(1,1) model represents the same specification as the ARCH(∞) model. Therefore, its necessary conditions are very similar to ARCH. Once again, to ensure positive variance of ε_t, $\alpha_0 > 0$ and $\alpha_1 \geq 0, \beta_1 \geq 0$. The condition $\alpha_1 + \beta_1 < 1$ has to be met for the volatility to be stationary.

3.3.3 TARCH models

The GARCH class of models described in the previous section has a theoretical limitation as to the sensitivity to the direction of change in the last piece of data. It has been shown that in some cases, the volatility of stock returns tends to be higher in case of a negative change than in case of a positive one (Engle, 2001, p.166).

The first model capable to accomodate for this difference was the EGARCH model, which is described for example in Tsay (2002). However, mainly in order of being able to directly compare the results of various models we will not deal with EGARCH model in this thesis.

Instead, we will use a simpler form of so called Threshold ARCH model (TARCH). The model we use has been introduced by Glosten et al. (1993) and it is sometimes called a GJR model. Its innovation is that it incorporates a dummy variable into the volatility equation. When we include it into the GARCH(1,1) model, the resulting equations are

$$\begin{aligned} &\varepsilon_t|\Psi_{t-1} \sim N(0, h_t) \\ &h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + I_\varepsilon\gamma_1\varepsilon_{t-1}^2, \end{aligned} \tag{3.21}$$

where

$$I_\varepsilon = \begin{cases} 1 & \text{if } \varepsilon_{t-1} > 0 \\ 0 & \text{otherwise} \end{cases}$$

Similarly as in the case of GARCH(1,1) model, conditions $\alpha_0 > 0, \alpha_1 + \gamma_1 \geq 0$ and $\beta_1 \geq 0$ have to be satisfied for the variance to be positive and the condition $\alpha_1+\beta_1+\gamma_1 < 1$ has to be met for the volatility to be stationary.

Chapter 4

Data description and tests

The existence of a dataset is absolutely crucial condition for performing empirical analyses. This chapter describes the origin and statistical properties of the stock indices and exchange rates data used in the empirical analysis. We also test for the stationarity of the data by running two tests described in section 3.1.1. Due to the nature of the data we examine its levels and first differences.

4.1 Exchange rates

Exchange rates against Euro were downloaded from the Eurostat database. The Euro was chosen because of having the highest relative importance from geographical, political and economical point of view. The vast majority of all countries' trade flows are conducted in Euros. Furthermore, all of the researched countries are expected to join the Eurozone up to a sooner or later time horizon. In fact, Slovenia and Slovakia already did.

Because all of the respected currencies have a smaller unit value than Euro, we define exchange rate as amount of local currency units per one Euro. Thus, an increase in the nominal exchange rate represents currency depreciation and vice versa.

The purpose of our analysis is to examine the influence of the exchange rate movement on the volatility of the stock market. It is thus crucial that the currency is allowed to float in a free way. This requires us to narrow down the sample to countries with national currencies not using fixed exchange rates, hence the sample includes currencies of Hungary, Czech Republic, Poland, Romania, Slovakia and Slovenia.

There are four currencies in our sample that followed a managed floating exchange rate during the whole period.These are Czech Koruna, Polish Zloty, Hungarian Forint and Romanian Leu. The koruna, zloty and forint are expected to join the ERM II[3] mechanism in the short to mid time horizon, however, they have not done so yet. It is interesting to mark that Czech Republic, Poland and Hungary are the three largest countries that joined the European Union on 1st of May 2004.

Romanian Leu has followed the managed floating exchange rate regime since 1997. However, the Leu has been devalued by a rate of 10 000:1 on 1st of July, 2005. The new currency is reffered to as New Romanian Leu. For the purpose of our analysis we report all the exchange rates since 1999 as converted to the New Romanian Leu.

As we are interested in floating currencies, we had to shorten the time span of the analysis in cases of Slovakia and Slovenia. Slovenian Tolar has been analyzed until June 28, 2004 and Slovak Koruna until November 25, 2005. Those are the dates when Slovenia and Slovakia joined the ERM II.

4.2 Stock market

As written above, the principle focus of our research is placed on the influence of the exchange rate changes on the stock market volatility. Although it does not take into account all of the stocks traded in a country, the stock market as a whole is generally represented by the main stock index in the researched country, so we will follow this principle.

Originally we intended to download the stock market data from Eurostat as well, but only the monthly data were available. Because the frequency of mothly data is too low

[3]ERM II is an exchange rate mechanism developed by European Union for countries preparing to join the Eurozone. In the moment of accepting Euro as their national currency, a country's disappearing currency must have been a part of ERM II for at least two years. The fluctuation band of ERM II is officially set to 15%, but the actual band is usually much more narrow.

for the type of analysis at hand, we had to look somewhere else. With the exception of Poland[4], we then managed to find the data at official websites of regarded stock exchanges.

A simple overview of stock market data is presented in table 4.1. The table also shows the period of research interest in all of the countries. As noted above, the default period of January 1999 to December 2009 had to be shortened in Slovakia and Slovenia for reasons regarding exchange rate regime shift.

Table 4.1: Stock market data overview

Country	Index	Source	Period
Czech Republic	PX	Prague Stock Exchange	Jan 04 1999 - Dec 31 2009
Hungary	BUX	Budapest Stock Exchange	Jan 07 1999 - Dec 31 2009
Poland	WIG	WSEinfospace	Jan 04 1999 - Dec 31 2009
Romania	BET	Bucharest Stock Exchange	Jan 01 1999 - Dec 31 2009
Slovakia	SAX	Bratislava Stock Exchange	Jan 07 1999 - Nov 25 2005
Slovenia	SBI20	Ljublana Stock Exchange	Jan 04 1999 - Jun 25 2004

4.3 Stationarity and unit root testing

As described in the section 3.1.1, stationarity is a very important concept and, to avoid spurious regression, it is absolutely crucial to make sure that our data are stationary. The usual consensus is that the financial series are nonstationary in levels, but contain a unit root. Therefore they can be transformed to stationary ones by first-differencing. This section tries to confirm validity of this consensus in our data.

We ran the Phillips-Perron test of logarithmic levels of exchange rates and stock market indices and their first differences. The test runs the null hypothesis of unit root against the alternative of stationarity. We also ran the KPSS test for 15 lags[5] which tests the null hypothesis of stationarity against the alternative of a unit root in order to

[4]In Poland we used WSEinfospace, an economic newswire created in cooperation of the Warsaw Stock Exchange and the Polish Press Agency (PAP) (REFERENCE - Web)

[5]The only exception is Slovakia, where the Schwert criterion chose the maximum lag order of 8, so the reported test statistics is for the 8th lag.

confirm our findings.

The critical values of the Phillips-Perron test are -2.570 for 10%, -2.860 for 5% and -3.430 for 1% level of confidence and the null hypothesis is rejected if the test statistics is more negative than the critical value. The critical values of KPSS test are 0.347 for 10%, 0.463 for 5% and 0.739 for 1% level of confidence.

4.3.1 Level data

The results of tests for level data are shown in table 4.2. According to the theory and usual consensus of researchers we should see insignificant results of Phillips-Perron tests and significant rejections of KPSS tests.

Table 4.2: Tests for stationarity: levels

	Exchange rate		Stock market	
Country	Phillips-Perron	KPSS	Phillips-Perron	KPSS
Czech Republic	-0.899	16***	-1.125	13.6***
Hungary	-2.937**	2.12***	-0.987	13.9***
Poland	-1.981	1.33***	-1.060	13.4***
Romania	-3.897***	12.1***	-1.608	15.2***
Slovakia	-0.992	15***	1.277	17.2***
Slovenia	-2.351	8.71***	0.896	7.87***

Note: *** and ** mark significance at 1% and 5% level of confidence.

We can see that the results are compatible with the theoretical expectation. Interesting result is the rejection of null hypothesis in the Phillips-Perron test in cases of Hungary and Romania, which can be a sign of so called fractional integration.

4.3.2 First differenced data

When we run both tests for first differenced logarithms, we should expect the rejection of the null hypothesis in the Phillips-Perron test and insignificant test statistics in the KPSS test. The results are presented in table 4.3.

Table 4.3: Tests for stationarity: differences

	Exchange rate		Stock market	
Country	Phillips-Perron	KPSS	Phillips-Perron	KPSS
Czech Republic	-52.354***	0.0536	-49.154***	0.191
Hungary	-52.297***	0.0343	-49.739***	0.109
Poland	-51.695***	0.0705	-49.812***	0.135
Romania	-49.191***	1.04***	-44.797***	0.438*
Slovakia	-38.135***	0.0822	-41.325***	0.547**
Slovenia	-68.153***	0.598**	-28.359***	0.347*

Note: ***, ** and * mark significance at 1%, 5% and 10% level of confidence.

The results of tests confirm the stationarity by a very strong rejection of the Phillips-Perron null hypothesis in all of the countries, with both exchange rate and stock market data. The KPSS test however also rejects the null hypothesis in case of Romania and and Slovenia for both exchange rate and stock market, and for Slovak exchange rate. This might again be a sign of so called fractional integration.

However, there is no simple technique how to account for the fractional integration of the data. Moreover, the statistics of Phillips-Perron tests of first differenced data are extremely significant. We have therefore decided to use the differenced data in our analysis.

4.4 Descriptive statistics

The descriptive statistics of exchange rate and stock index first differenced time series are shown in table 4.4. We can see that the fourth moment, kurtosis, is higher than three in all of the series. This implies that the statistical distribution of the data has thicker tails compared to the normal distribution, a phenomenon known as leptokurtosis. It has been shown that leptokurtosis is widely present in financial time series.

In addition, all series are skewed to some extent. All of the stock market series except of Slovenian show negative skewness, meaning that the relatively higher mass of distribution lies on its right side. This is not surprising since the stock market indices were

Table 4.4: Descriptive statistics of first difference of log daily data

	Czech Republic	Hungary	Poland	Romania	Slovenia	Slovakia
Stock Indices						
Minimum	-.1618547	-.1264895	-.0846784	-.1311676	-.0476735	-.1148386
Maximum	.1236405	.1317775	.0680388	.1009072	.0831093	.0595906
Mean	3.678e-04	4.048e-04	.0003931	.0008792	.0006924	.0008779
Standard dev.	.0155325	.0168224	.0144789	.0178966	.0070953	.0137755
Variance	.0000169	.000283	.0002096	.0003203	.0000503	.0001898
Skewness	-.4589364	-.1098388	-.2224103	-.3707849	1.118297	-.5894101
Kurtosis	15.09851	9.054811	5.70942	8.919612	19.69696	9.903126
Jarque-Bera	1.7e+04	4316	884.6	4198	1.7e+04	3603
	(0)	(0)	(8.e-193)	(0)	(0)	(0)
Exchange rates						
Minimum	-.0327446	-.03385	-.036798	-.0987312	-.0170692	-.0165124
Maximum	.0316496	.0506931	.041636	.1123351	.0162895	.0185003
Mean	-9.99e-05	2.77e-05	2.89e-06	.0004143	.0001687	-.0000567
Standard dev.	.00417	.0055814	.0068515	.0068798	.0016505	.0029031
Variance	.0002413	.0000312	.0000469	.0000473	2.72e-06	8.43e-06
Skewness	.3021535	.0958891	.484135	1.113254	.1179574	.7165732
Kurtosis	9.958144	14.37771	7.738888	46.48663	32.79899	8.43007
Jarque-Bera	5742	1.6e+04	2745	2.2e+05	5.2e+04	2317
	(0)	(0)	(0)	(0)	(0)	(0)
Observations	2825	2822	2816	2831	1406	1763

Note: The numbers in parenthesis represent the p-values of Jarque-Bera test for normality of the data showing a relatively stable growth during the most of the researched time period. To the contrary, all exchange rate series show positive skewness.

The last two rows of both main panels in the table 4.4 show Jarque-Bera test of normality of the data. All of the test statistics are highly significant, rejecting the null hypothesis of normality at almost any reasonable level of confidence (the highest p-value found was 9.1e-16). This result is not surprising if we take into account the information of the last two paragraphs.

4.5 Autocorrelation

In order to be able to use ARCH class of models we need to confirm that the autocorrelation is present in the data. As has been noted in the section 3.3, we will use a Ljung-Box test with 15 lags in order to find a presence of conditional heteroscedasticity in the data. Because we are going to model the stock market using exchange rate as an explanatory variable, we only report the test results for the first differenced log stock market changes and its squares.

Table 4.5: Ljung-Box test of stock market data

Country	s_t	s_t^2
Czech Republic	40.2643***	2979.8330***
Hungary	80.5036***	1653.8172***
Poland	21.6712	756.9504***
Romania	97.6732***	1183.4853***
Slovakia	14.2344	73.4960***
Slovenia	157.7195***	120.4427***

Note: *** mark significance at 10% level of confidence

The table 4.5 reports the results of Ljung-Box test with 15 lags. The results of Czech Republic, Hungary, Romania and Slovenia are highly significant in both changes and squared changes, leading to a presence of ARCH in the data. The results of Poland and Slovakia are not significant in changes. On the other hand, the very significant statistics of squared changes suggest that there is an autocorrelation present in the data.

In order to confirm this finding, we have to examine the autocorrelation function (ACF) of the data. The results for Poland show the first three lags significant at 1%, the first six at 5% and the first nine at 10% levels of confidence therefore we can assume that the ARCH process is present in the Polish data as well.

The Slovak ACF function unfortunately fails to report any significant lags of variables. However, as to the presence of autocorrelation in the squared data and to ensure using the same empirical methods to examine the nature of our data, we have decided to use the ARCH framework also in the Slovak case.

Chapter 5

Models and interpretations

In this chapter we estimate the coefficients of several conditional heteroskedastic models in order to describe the properties of stock indices in researched countries. The main two topics we examine is the influence of the exchange rate change on the stock market volatility and whether or not this volatility differs with positive and negative changes of the index.

The first section shows that we can use the GARCH(1,1) specification while observing the stock market volatility. Then we estimate the coefficients of the basic GARCH(1,1) model. Afterwards we include the explanatory variable of exchange rate change in order to look for possible influence that it could have. Finally, we include a TARCH term in order to test whether the sign of change is important in explaining stock index volatility.

Similarly as in Fidrnuc & Horváth (2008), we have decided not to include any additional explanatory variables into our mean equation. It will thus only consist of a constant and error term.

For the reasons of putting an explanatory variable into the volatility equation all the computations are provided by the Stata package. When it was possible, we have also checked the validity of our results by comparing them to the results of JMulTi.

5.1 From ARCH to GARCH

Empirical series often have slowly decaying autocorrelation function, which results into a need of a high order ARCH process while modeling them. However, the model can be usually simplified by adding lags of the variance estimator, which is the innovation of GARCH model. Nobel Prize Committee (2003) states that the first order GARCH term is usually enough to describe the data. This section tries to verify this assumption on our data.

We estimated five models for each country: first to fourth order ARCH and GARCH(1,1). We compared their Akaike's information criteria to find out which model fits the data in the best way. The more negative Aikaike's information criterion is, the better fit our model produces.

Table 5.1: Comparison of Akaike Information Criteria

Country	ARCH(1)	ARCH(2)	ARCH(3)	ARCH(4)	GARCH(1,1)
Czech Rep.	-15791.42	-16236.48	-16380.08	-16432.59	-16618.11
Hungary	-15275.67	-15394.66	-15511.05	-15552.74	-15733.04
Poland	-15917.33	-15967.39	-16091.56	-16194.99	-16322.72
Romania	-15320.66	-15447.69	-15490.85	-15506.38	-15623.14
Slovakia	-10115.86	-10145.81	-10171.6	-10177.47	-10235.73
Slovenia	-10259.84	-10301.18	-10338.77	-10336.77	-10341.2

The results are shown in table 5.1. In all countries (with the only exception of third-to-fourth lag in Slovenia) the next model was found to be better in terms of fit. The results clearly show that for all countries the GARCH(1,1) model fits the data better than any of the ARCH models up to fourth order. The very same applies for Bayesian information criterion, which we do not report here.

We have also compared Akaike's information criteria of the GARCH(1,1) model with ones of GARCH(2,1) and GARCH(1,2) models. The levels of criteria was directly comparable in all three models. In fact, the Akaike's and Bayesian information criteria were contradictory, as sometimes the AIC showed an improvement, whereas BIC did not, and vice versa. This result leads us to a conclusion that GARCH(1,1) provides an optimal fit in class of simple ARCH and GARCH models.

5.2 Basic GARCH model

As shown in section 3.3.2, the condition $\beta + \gamma < 1$ has to be met in order for the volatility to be stationary, e.g., not to grow into infinity. Therefore, as a first step, we need to evaluate coefficients of the simple GARCH(1,1) process in stock market data before we proceed to the additional analysis. The model is represented by equation

$$\begin{aligned} s_t &= \mu + \varepsilon_t \\ \varepsilon_t &\sim N(0, h_t) \\ h_t &= \alpha + \beta \varepsilon_{t-1}^2 + \gamma h_{t-1}, \end{aligned} \tag{5.1}$$

where s_t stands for the first order logarithmic difference of stock index at time t. The results are shown in table 5.2.

The level of the constant in the mean equation is small but significantly positive for all countries. This result was expected taken into account that the mean of the data is also small and positive.

We can see that the level of γ is generally relatively higher than the level of β, which corresponds to results of e.g. Bollerslev (1986) or Nobel Prize Committee (2003) and is also consistent with the interpretation of GARCH component taking the role of significant higher-order ARCH components. For example in Polish and Slovakian case the results indicate that 93% of the conditional variance in time $t-1$ are influential for the conditional variance in time t. Thus, the potential shocks are relatively persistent.

The only exception to this is Slovenia, where the ARCH term has almost the same magnitude as the GARCH term. This means that if we would have had to use only ARCH class of models, the order of a Slovenian one would most probably be the lowest one among our countries. This corresponds to our result from section 5.1, where we found that changing the model from ARCH(3) to ARCH(4) does not improve the model's fit in Slovenian case.

Table 5.2: Results of basic GARCH estimation

	Czech Republic	Hungary	Poland	Romania	Slovenia	Slovakia
μ	.0009677***	.0007885***	.0007463***	.0013284***	.0004435***	.0006959**
	(4.53)	(3.00)	(3.29)	(5.03)	(2.97)	(2.16)
α	4.77e-06***	5.44e-06***	2.06e-06***	.0000131***	6.24e-06***	4.21e-06***
	(5.88)	(5.22)	(4.24)	(12.7)	(7.30)	(8.57)
β	.1245265***	.0842687***	.0596931***	.1769524***	.4343307***	.0458236***
	(11.55)	(10.28)	(10.9)	(19.59)	(11.92)	(9.55)
γ	.8559587***	.8946436***	.9307842***	.7893871***	.4976539***	.9329431***
	(69.52)	(92.43)	(148.97)	(19.59)	(14.09)	(168.84)
AIC	-16618.11	-15733.04	-16322.72	-15623.14	-10341.2	-10235.73

Notes: The table shows estimates of the coefficients from equation 5.1.
The numbers in parentheses under estimates show their z-statistics.
*** and ** mark significance at 1% and 5% level of confidence.

Another important implication is that in all countries it holds that $\beta + \gamma < 1$, which ensures that the volatility is stationary. Moreover, their sum is very close to one, which indicates that the process is mean-reverting very slowly (Engle, 2001). Such result is very common in empirical applications (Nobel Prize Committee, 2003).

Although we report the levels of Akaike's information criteria below the estimates of model parameters, it is important to acknowledge that the absolute level of AIC is not comparable among different datasets. However, we will be able to compare AIC's from the last model with the ones from models below.

5.3 GARCH model

To examine the impact of exchange rate change on the volatility of stock market, we need to adjust the volatility equation 3.20 by adding additional term, resulting in the equation

$$\begin{aligned} s_t &= \mu + \varepsilon_t \\ \varepsilon_t &\sim N(0, h_t) \\ h_t &= \alpha + \beta\varepsilon_{t-1}^2 + \gamma h_{t-1} + \delta r_t, \end{aligned} \tag{5.2}$$

where s_t again stands for the first order logarithmic difference of stock index at time t and r_t represents the first order logarithmic difference of exchange rate at time t.

However, the Stata software package does not allow us to estimate this type of equation. Therefore we need to change the model to allow for multiplicative heteroscedasticity. The proposed model will thus estimate coefficients of the equation

$$\begin{aligned} s_t &= \mu + \varepsilon_t \\ \varepsilon_t &\sim N(0, h_t) \\ h_t &= \exp(\alpha + \delta r_t) + \beta\varepsilon_{t-1}^2 + \gamma h_{t-1}. \end{aligned} \tag{5.3}$$

The results are shown in table 5.3. Estimates of coefficients μ, β and γ are very similar to the coefficients of equation 5.1 that are reported in table 5.2. Estimates of coefficient α differ very much, however, given that the coefficient α was included into the exponential

Table 5.3: Results of GARCH estimation

	Czech Republic	Hungary	Poland	Romania	Slovenia	Slovakia
μ	.0009739***	.0008366***	.0007669***	.0013221***	.0004484***	.0006966**
	(4.54)	(3.15)	(3.37)	(5.03)	(3.00)	(2.16)
α	-12.20061***	-11.97751***	-12.69118***	-11.2329***	-12.01866***	-12.3752***
	(-73.89)	(-62.01)	(-61.73)	(-143.82)	(-85.25)	(-104.56)
δ	117.355***	75.60301***	105.8885***	-28.42695**	86.32077	13.27948
	(5.02)	(6.67)	(9.54)	(-2.51)	(0.92)	(0.14)
β	.1260259***	.0851941***	.0646084***	.1795259***	.4301188***	.0457774***
	(11.43)	(9.64)	(9.84)	(19.59)	(12.03)	(9.28)
γ	.8500117***	.8868414***	.9146508***	.7865166***	.5020737***	.9329343***
	(67.28)	(81.50)	(113.63)	(87.26)	(14.26)	(162.30)
AIC	-16620.77	-15740.36	-16337.17	-15622.84	-10339.58	-10233.74

Notes: The table shows estimates of the coefficients from equation 5.3.
The numbers in parentheses under estimates show their z-statistics.
*** and ** mark significance at 1% and 5% level of confidence.

function, their interpretation is very same. Moreover, the relatively biggest coefficient from equation 5.1 (the Hungarian one) is the least negative one in equation 5.3.

The estimated values of parameter δ are interesting. The positive values for Czech Republic, Hungary and Poland suggest that the currency depreciation tends to increase the stock market volatility in those three countries and vice versa. On the other hand, the results from Romania suggest exactly the opposite. In Romania the stock market volatility is higher after currency appreciation and vice versa. The estimates for Slovakia and Slovenia are insignificant.

Comparing Akaike's information criteria, we can see improvement of the fit of the model for the Czech Republic, Hungary and Poland. Interestingly, those are the same countries that reported statistically significant positive coefficient δ. On the other hand, even though the AICs for Romania, Slovenia and Slovakia are less negative than in the case of previous model, the difference is quite small so we can assume that both models fit the data approximately the same.

5.4 One additional step: a TARCH model

It has been shown that stock market indices tend to show tendencies to have a different volatilities in case of a positive and negative changes (Engle, 2001). The TARCH model allows to generalize the previous GARCH model to account for this phenomenon. We will estimate the equation

$$\begin{aligned} s_t &= \mu + \varepsilon_t \\ \varepsilon_t &\sim N(0, h_t) \\ h_t &= \exp(\alpha + \delta r_t) + \beta \varepsilon_{t-1}^2 + \gamma h_{t-1} + I_\varepsilon \lambda \varepsilon_{t-1}, \end{aligned} \tag{5.4}$$

where

$$I_\varepsilon = \begin{cases} 1 & \text{if } \varepsilon_{t-1} > 0 \\ 0 & \text{otherwise} \end{cases}$$

Because the estimates of parameter δ were found insignificant in case of Slovakia and

Slovenia, we have decided not to include it into the reported analysis [6]. The volatility equation of the model for Slovakia and Slovenia will thus take form of

$$h_t = \alpha + \beta\varepsilon_{t-1}^2 + \gamma h_{t-1} + I_\varepsilon \lambda \varepsilon_{t-1}. \tag{5.5}$$

The results are shown in table 5.4. Again, the values of coefficients $\mu, \alpha, \beta, \gamma$ and δ (where applicable) are very similar to the values from previous models.

The TARCH component was found to be significant in five of six countries, even though for Slovenia only at the 10% level of confidence. This result is in line with previous empirical research, e.g. the one of Jiang & Chiang (2000). The results of Czech Republic, Hungary and Poland suggest that the drop in the stock index value has additional increasing effect on its volatility which is compatible with the usual consensus. On the other hand, the results of the Slovenia and Slovakia suggest that the stock index volatility tends to be higher after the 'good news' rather than 'bad news'.

[6] When we estimated the model including the coefficient δ the results were almost the same in terms of values and exactly the same in terms of siginificance. The z-values of TARCH terms changed from 1.83 to 1.82 in Slovenia and from 2.34 to 2.33 in Slovakia.

Table 5.4: Results of TARCH estimation

	Czech Republic	Hungary	Poland	Romania	Slovenia	Slovakia
μ	.0007514***	.0005785**	.0006884***	.0012581***	.0004885***	.0007559**
	(3.38)	(2.17)	(2.95)	(4.64)	(3.12)	(2.30)
α	-11.95358***	-11.84513***	-12.65465***	-11.19506***	6.32e-06***	4.38e-06***
	(-82.43)	(-65.61)	(-63.06)	(-139.66)	(7.20)	(8.25)
δ	115.385***	67.92835***	101.5081***	-27.85011**	n/a	n/a
	(6.04)	(5.49)	(8.42)	(-2.41)		
β	.1681296***	.1172748***	.075013***	.192998***	.3818058***	.0364445***
	(10.91)	(8.96)	(9.24)	(13.68)	(8.81)	(6.29)
γ	.8397611***	.8835425***	.9143321***	.7825986***	.4960732***	.9325128***
	(61.58)	(78.21)	(111.81)	(82.76)	(13.55)	(157.60)
λ	-.0864105***	-.0649356***	-.0212709**	-.0228266	.0984505*	.0176831**
	(-6.06)	(-5.15)	(-2.29)	(-1.46)	(1.83)	(2.34)
AIC	-16640.56	-15759.74	-16338.71	-15621.87	-10341.31	-10236.3

Notes: The table shows estimates of the coefficients from equation 5.4. In case of the last two collumns the volatility equation 5.5 applies.
The numbers in parentheses under estimates show their z-statistics.
***, ** and * mark significance at 1%, 5% and 10% level of confidence.

Chapter 6

Conclusion

The results of our analysis are broadly compatible with results of the previous research. Our results indicate that the effect of exchange rate changes on stock market volatility differs among countries. We have found out that an exchange rate depreciation will boost stock market volatility in Czech Republic, Hungary and Poland, and vice versa. On the other hand, currency appreciation will do the same in Romania.

It is interesting to mark that the coefficient λ from our TARCH model is significantly negative in the same three countries where the coefficient δ marking the exchange rate influence is positive. This can be interpreted in a way that markets that are sensitive to exchange rate changes are also sensitive to the direction of change in the stock return.

We have also found out that the volatility of the stock market is persistent for all countries except for Slovenia. The sum of GARCH coefficients is close to one for all countries, suggesting that the stock index processes are mean reverting very slowly.

We have confirmed that stock market indices and exchange rates of all countries in the sample contain one unit root. Moreover, the results of the Jarque-Bera test for normality indicate that the data are not normal and contain leptocurtic distribution, a phenomenon that has been widely present in financial data.

It is also important to note that our model has an important limitation. Namely, it tests for the presence of causality from exchange rate changes to stock market volatility but it is ignoring possible existence of the causality from the other side. As a suggestion for future research, we would therefore try to implement a model that could account for causalities of both directions. One possible way how to do it would be implementing a multivariate EGARCH model. Such an implementation would also make the model directly comparable to the models of De Santis & Gérard (1998) and Choi et al. (2007).

References

Abdalla, I. S. A. & Murinde, V. (1997). Exchange Rate and Stock Price Interactions in Emerging Financial Markets: Evidence on India, Korea, Pakistan and the Philippines. *Applied Financial Economics*, *7*(1), 25–35.

Ajayi, R. A. & Mougoue, M. (1996). On the Dynamic Relation between Stock Prices and Exchange Rates. *Journal of Financial Research*, *19*(2), 193–207.

Alaganar, V. T. & Bhar, R. (2007). Empirical properties of currency risk in country index portfolios. *The Quarterly Review of Economics and Finance*, *47*(1), 159–174.

Aydemir, O. & Demirhan, E. (2009). The Relationship between Stock Prices and Exchange Rates: Evidence from Turkey. *International Research Journal of Finance and Economics*, *23*, 207–215.

Bartov, E., Bodnar, G. M., & Kaul, A. (1996). Exchange rate variability and the riskiness of U.S. multinational firms: Evidence from the breakdown of the Bretton Woods system. *Journal of Financial Economics*, *42*(1), 105–132.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327.

Brooks, C. (2008). *Introductory Econometrics for Finance* (1st ed.). Cambridge, UK: Cambridge University Press.

Choi, D. F. S., Fang, V., & Fu, T. Y. (2007). Volatility spillovers between stock market returns and exchange rate changes: the New Zealand case. Conference paper, MODSIM

2007 International Congress on Modelling and Simulation, Christchurch, New Zealand; 10-13 December, 2160-2167.

De Santis, G. & Gérard, B. (1998). How big is the premium for currency risk? *Journal of Financial Economics*, *49*(3), 375–412.

Dimitrova, D. (2005). The Relationship between Exchange Rates and Stock Prices: Studied in a Multivariate Model. *Issues in Political Economy*, *14*.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*(4), 987–1007.

Engle, R. F. (2001). GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. *Journal of Economic Perspectives*, *15*(4), 157–168.

Engle, R. F. (2003). Risk and Volatility: Econometric Models and Financial Practice. Nobel Prize in Economics documents 2003-4, Nobel Prize Committee.

Fidrnuc, J. & Horváth, R. (2008). Volatility of Exchange Rates in Selected New EU Members: Evidence from Daily Data. *Economic Systems*, *32*, 103–118.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, *48*(5), 1779–1801.

Granger, C. W. J., Huangb, B.-N., & Yang, C.-W. (2000). A bivariate causality between stock prices and exchange rates: evidence from recent Asian flu. *The Quarterly Review of Economics and Finance*, *40*(3), 337–354.

Granger, C. W. J. & Newbold, P. (1974). Spurious Regressions in Econometrics. *Journal of Econometrics*, *2*(2), 111–120.

Hamilton, J. D. (1994). *Time series analysis.* Princeton: Princeton University Press.

Jiang, C. & Chiang, T. C. (2000). Do Foreign Exchange Risk Premiums Relate to the Volatility in the Foreign Exchange and Equity Markets? *Applied Financial Economics*, *10*(1), 95–104.

Kanas, A. (2000). Volatility Spillovers Between Stock Returns and Exchange Rate Changes: International Evidence. *Journal of Business Finance & Accounting*, *27*(3 & 4), 447–467.

Kasman, S. (2003). The Relationship between Exchange Rates and Stock Prices: A Causality Analysis. *Dokuz Eylul University Journal of Graduate School of Social Sciences*, *5*(2), 70–79.

Kyung-Chun, M. (2008). Effects of Exchange Rate Fluctuations on Equity Market Volatility and Correlations: Evidence from the Asian Financial Crisis. *Quarterly Journal of Finance and Accounting*, *47*(3), 77–102.

Ma, C. K. & Kao, G. W. (1990). On Exchange Rate Changes and Stock Price Reactions. *Journal of Business Finance & Accounting*, *17*(3), 441–449.

Nieh, C.-C. & Lee, C.-F. (2001). Dynamic relationship between stock prices and exchange rates for G-7 countries. *The Quarterly Review of Economics and Finance*, *41*(4), 477–490.

Nobel Prize Committee (2003). Time-series Econometrics: Cointegration and Autoregressive Conditional Heteroskedasticity. Nobel Prize in Economics documents 2003-1, Nobel Prize Committee.

Scheicher, M. (2001). The Comovements of Stock Markets in Hungary, Poland and the Czech Republic. *International Journal of Finance & Economics*, *6*(1), 27–39.

Tsay, R. S. (2002). *Analysis of financial time series* (1st ed.). John Wiley & Sons.

Verbeek, M. (2008). *A Guide to Modern Econometrics* (3rd ed.). John Wiley & Sons.

UNIVERSITAS CAROLINA PRAGENSIS
založena 1348

Univerzita Karlova v Praze
Fakulta sociálních věd
Institut ekonomických studií

Opletalova 26
110 00 Praha 1
TEL: 222 112 330,305
TEL/FAX: 222 112 304
E-mail: ies@mbox.fsv.cuni.cz
http://ies.fsv.cuni.cz

Akademický rok 2008/2009

TEZE BAKALÁŘSKÉ PRÁCE

Student:	Radek Janhuba
Obor:	Ekonomie
Konzultant:	Roman Horváth, Ph.D.

Garant studijního programu Vám dle zákona č. 111/1998 Sb. o vysokých školách a Studijního a zkušebního řádu UK v Praze určuje následující bakalářskou práci

Předpokládaný název BP:

The effects of exchange rate changes on stock market in post-transition countries

Charakteristika tématu, současný stav poznání, případné zvláštní metody zpracování tématu:

The purpose of the thesis is to examine the effects of exchange rate movements on the stock market trade with an orientation towards post-transition countries. Based on the survey of the literature, I would like to create a multivariate regression model with stock market trade as the dependent variable. The model will then be used for selected countries to find out if and how the exchange rates influence the stock market trade, and whether there is any difference depending on if the country is or is not a post-transition one.

Struktura BP:

1. Introduction
2. Literature overview (previous research)
3. Regression model (Independent variables, dummy variables, sources)
4. Interpretation of the results
5. Conclusion

Seznam základních pramenů a odborné literatury:

Abdalla, I S A, & Murinde, V (1997): "Exchange rate and stock price interactions in emerging financial markets: evidence on India, Korea, Pakistan and Philippines". Applied Financial Economics, 7, 25-35.

Ajayi, A R, and Mougoue, M (1996): "On the dynamic relation between stock prices and exchange rates". The Journal of Financial Research, Vol. 19, 193-207.

Baharom, A H, Royfaizal, R C & Habibullah, M S (2008): "Causation analysis between stock price and exchange rate: Pre and post crisis study on Malaysia," MPRA Paper 11925, University Library of Munich, Germany. http://mpra.ub.uni-muenchen.de/11925/

Bailey, W & Chung, Y P (1995): "Exchange Rate Fluctuations, Political Risk, and Stock Returns: Some Evidence from an Emerging Market". *Journal of Financial and Quantitative Analysis*, vol. 30(04), pp. 541-561

Dimitrova, D. (2005): "The Relationship between Exchange Rates and Stock Prices: Studied in a Multivariate Model". Issues in Political Economy, Vol. 14 http://org.elon.edu/ipe/Dimitrova%20final.pdf

Fidrmuc, J & Horváth, R (2008): "Volatility of Exchange Rates in Selected EU New Members: Evidence from Daily Data". *Economic Systems*, 32 (1), 103-118.

Ihrig, J & Prior, D (2005): "The effect of exchange rate fluctuations on multinationals' returns". *Journal of Multinational Financial Management*, vol. 15(3), pages 273-286

Jiang, C & Chiang, T C (2000): "Do Foreign Exchange Risk Premiums Relate to the Volatility in the Foreign Exchange and Equity Markets?". *Applied Financial Economics*, vol. 10(1), pages 95-104.

Kasman, S (2003): "The Relationship Between Exchange Rates and Stock Prices: A causality Analysis" http://www.sbe.deu.edu.tr/adergi/2003sayi2PDF/kasman.pdf

Kočenda, E., 2005. Beware of Breaks in Exchange Rates: Evidence from European Transition Countries. Economic Systems, 29(3), 307-324. ISSN 0939-3625. http://home.cerge-ei.cz/kocenda/papers/ExrBreaks.pdf

Nieh, C C & Lee, C F (2001): "Dynamic relationship between stock prices and exchange rates for G-7 countries". The Quarterly Review of Economics and Finance, Vol. 41(4), 477-490.

Poghosyan, T., Kočenda, E., 2009. Macroeconomic Sources of Foreign Exchange Risk in New EU Members. Forthcoming in Journal of Banking and Finance. ISSN: 0378-4266. http://home.cerge-ei.cz/kocenda/papers/MGM.pdf

Scheicher, M., 2001. The Comovements of Stock Markets in Hungary, Poland and the Czech Republic. International Journal of Finance and Economics 6(1), 27-39.

Syriopoulos, T., 2004. International Portfolio Diversification to Central European Stock Markets. Applied Financial Economics 14(17), 1253-68.

Datum zadání:	červen 2009
Termín odevzdání:	červen 2010

Podpisy konzultanta a studenta:

V Praze dne